Comparative Study of Intelligent and Classical MPPT Techniques Applied to Solar Battery Charger

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Abstract. Renewable solar energy is an excellent alternative to conventional energy sources and has recently shown remarkable growth in electrical power grids worldwide. Maximum power point tracking (MPPT) is critical in solar energy generation as it enhances system efficiency. Photovoltaic (PV) modules are affected by environmental factors like temperature and solar irradiation, altering the energy generated throughout the day. To extract maximum power from a PV, MPPT techniques consider system nonlinearities. MPP is achieved by adjusting the duty cycle of the DC-DC converter to align the PV's terminal voltage with environmental conditions, typically relying on voltage and current sensors due to their low cost and ease of acquisition. However, intelligent techniques often require additional temperature and irradiation sensors, increasing system complexity. Recent publications highlight the significant efficiency gains from intelligent control techniques in energy generation. This study aims to develop and simulate a battery charging system using solar energy in MATLAB/SIMULINK, comprising a PV, a Buck converter, a 12V battery, and an MPPT controller. The study compares the intelligent fuzzy logic MPPT technique (Fuzzy MPPT) and the classical incremental conductance technique (IC MPPT), both utilizing only voltage and current measurements.

Keywords: Maximum Power Point Tracking; Solar Battery Charger; Fuzzy System;

1 Introduction

As awareness of sustainability and mitigating climate change grows, renewable energy sources are being sought after as a vital tool for cutting greenhouse gas emissions. In this context, solar energy is a popular alternative clean energy source that can be utilized for industrial, commercial, and residential applications. Utilizing photovoltaic panel-related technologies, such as battery storage, which enables the continuing use of the energy captured even at night or on cloudy days, can improve the system's efficiency. Inverters, DC-DC converters, and sophisticated monitoring systems are examples of emerging electronic technologies that significantly improve efficiency.

The photovoltaic panel (PV) develops a nonlinear behavior that depends on the environmental factors of temperature and irradiation. These parameters modify the power profiles available for extraction from the PV, changing the operating points corresponding to their maximum value (MPP). In this sense, various Maximum Power Point Tracking (MPPT) techniques have been developed and widely used in this context. Algorithms such as hill climb (HC), perturb and observe (P&O), and incremental conductance (IC) are some of the classic methods used in photovoltaic systems [1].

Despite their easy implementation and low complexity, they are often singled out for having a characteristically slow response time to sudden changes in weather conditions or more complex operating conditions such as the partial shading condition (PSC). Therefore, Intelligent MPPT techniques have been developed to obtain a more robust, efficient and flexible system. Among them, fuzzy inference systems (FIS) have had a notable presence in the literature over the last few decades as an easy-to-tune system, since it does not require analytical knowledge of the systems, and are reliable for dealing with nonlinearities [2]. The use of the fuzzy MPPT technique has a significant presence, particulary when applied to photovoltaic power generation systems, where various studies have explored its flexibility and characteristics in this area [3–7].

In [8] they use, in addition to the traditional P-V curve of the panel, the I-V curve, where the derivatives of each curve are used as input variables for the fuzzy inference system (FIS).In [9], which uses power and voltage variations and a beta factor (related to voltage and current values) as inputs, exploring alternatives for the number and type of fuzzy input variables. Moreover in [10], which explores how the various existing pertinence functions (Trapezoidal, triangular, Gaussian, etc.) impact on the tracking process.

In this regard, this paper contributes as follows:

- Analysis of the nonlinear PV model;
- Static design of the Buck converter operating as a solar battery charger;
- Design of the fuzzy MPPT considering the variable duty-cycle increment;
- Detailed description of the performance parameters;
- Simulation and comparative analysis of the results considering the fuzzy MPPT and IC MPPT techniques focused on the difference between variable increment versus fixed increment.

In terms of structure, this paper is as follows: section 2 describes the characteristics of the PV and its equivalent circuit that models the nonlinear behavior. In section 3 is provided the Buck converter design requirements, considering its operation as a solar battery charger and the definition of the components. Section 4 provides a brief description of the classic MPPT IC technique. In section 5, the detailed implementation of the proposed fuzzy MPPT is described. The simulation results of the proposed MPPTs under various environmental conditions is shown in section 6. The last section includes the concluding remarks.

2 PV Modeling

PV cells have a nonlinear behavior represented by the I-V and P-V characteristic curves. Additionally, [11] proposes an equivalent circuit that represents the nonlinear behavior of PV cells, as shown in Fig. 1. R_s is the cell's series resistance, R_p is the cell's parallel resistance, and D_{pv} characterizes the semiconductor junction of the material from which the cells are made, typically silicon. i_{ph} represents the photocurrent induced in the cells, described by eq. (1), and it is a function of the cell's temperature ($temp$) and solar irradiation (p_{sun}).

$$i_{ph}(p_{sun}, temp) = [I_{SC} + \alpha \cdot (temp - T_r)] \cdot \frac{p_{sun}}{1000} \tag{1}$$

I_{SC} is the cell's short-circuit current, α is I_{sc}'s temperature coefficient, and T_r is the reference temperature (25 °C = 298 K). The eq. (2) is an expression that approximates the characteristic behavior of the PV current and described as a function of 3 variables: solar irradiance (p_{sun}), temperature ($temp$), and PV cell voltage (v_{pv}), which was obtained from expanding the exponential terms in the Taylor's series results in the standard operation point (1000 W/m^2 and 298 K). Where k is the Boltzmann's constant, q is the elementary charge, n is the quality factor of the junction, and $I_{rr} = 7.154$ pA is the reference reverse saturation current.

$$i_{pv}(p_{sun}, temp, v_{pv}) = \frac{i_{ph}(p_{sun}, temp) - I_{rr} \cdot (e^{\frac{q \cdot v_{pv}}{n \cdot k \cdot T_r}} - 1) - \frac{v_{pv}}{R_p}}{1 + \frac{R_s}{R_p} + \frac{I_{rr} \cdot q \cdot R_s}{n \cdot k \cdot temp} \cdot e^{\frac{q \cdot v_{pv}}{n \cdot k \cdot T_r}}} \tag{2}$$

Therefore, given any operating condition, by controlling v_{pv}, it is possible to find the corresponding MPP, which is called MPPT. The PV parameters were specified according to 330W commercial modules.

3 Buck Converter Design

The Fig. 1 contains the equivalent circuit of the solar battery charger consisting of PV, Buck converter and Battery. This system is controlled by the MPPT algorithm that uses the v_{pv} and i_{pv} signals to adjust the duty-cycle (D_t) that controls the S switch from the PWM modulator, in order to deliver the maximum available energy to the battery.

The component specifications are contained in Table 1, obtained according to equations 3, 5, 4 to meet the design requirements of output current ripple ($\Delta I_o = 10$ %), and input voltage ripple, and output voltage ripple ($\Delta V_{in} = \Delta V_o = 1$ %). Where f_s is the converter's switching frequency (150 kHz), D_{min} is

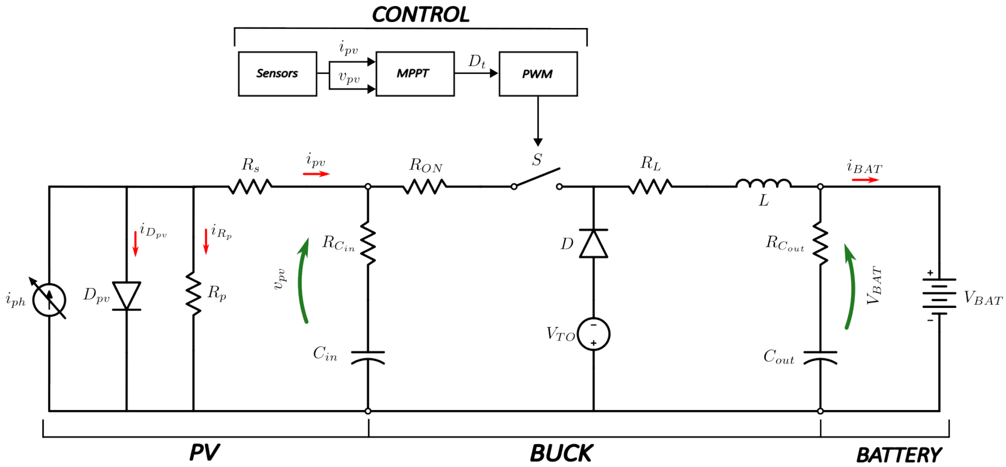


Figure 1. System Overview

the duty-clyce corresponding to the 50 V input voltage ($D_{min} = 12/50 = 0.24$) and D_{max} corresponding to the 20 V input voltage ($D_{max} = 12/20 = 0.6$).

$$L = \frac{V_o(1 - D_{min})}{\Delta I_L \cdot fs} = 22.109\ \mu H \tag{3}$$

$$\Delta V_{C_{out}} = (\frac{1}{8 \cdot C_{out} \cdot fs} + R_{C_{out}}) \cdot \Delta I_o \tag{4}$$

$$\Delta V_{C_{in}} = (\frac{(1 - D_{max}) \cdot D_{max}}{C_{in} \cdot fs} + R_{C_{in}}) \cdot \Delta I_o \tag{5}$$

Table 1. Buck Parameters

Description	Symbol	Value
Inductor	L	22.109 μ H
Internal Inductor Resistance	R_L	3 mΩ
Input Capacitor	C_{in}	2.7 mF
Internal Resistance of C_{in}	$R_{C_{in}}$	6.519 mΩ
Output Capacitor	C_{out}	500 μF
Internal Resistance of C_{out}	$R_{C_{out}}$	35.2 mΩ
Diode Forward Voltage	V_{TO}	1 V
MOSFET Conduction Resistance	R_{ON}	6.5 mΩ

4 IC MPPT

To implement the MPPT IC, the input variables considered were v_{pv} and i_{pv}. Thus, the classic IC algorithm was used, assuming that in MPP the eq. (6) is valid [1].

$$\frac{dP}{dV} = 0, \frac{dI}{dV} = -\frac{I}{V} \tag{6}$$

Additionally, based on the voltage increment to be given, duty increment ($\Delta D = 0.0001$) is defined as a constant value. According to the buck converter logic: a positive voltage increment results from a negative duty increment, and a negative voltage increment results from a positive duty increment.

5 Fuzzy MPPT

The following quantities were used as input variables to implement the fuzzy inference system as an MPPT, the power derivative about the voltage, referred to as the error (E), eq. (7), and its variation (ΔE), eq. (8). The duty increment (ΔD), eq. (9) was defined as the output variable, where t is the simulation step.

$$E_t = \frac{dP_{pv}(t)}{dV_{pv}(t)} \tag{7}$$

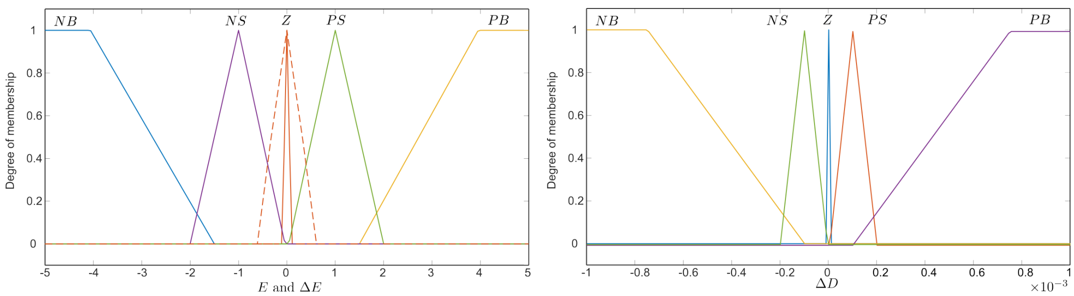
$$\Delta E_t = E_t - E_{t-1} \tag{8}$$

$$D_t = D_{t-1} + \Delta D_t \tag{9}$$

The derivative of the power indicates, by its magnitude and sign, the location of the instantaneous point of the P_{MPP}/V_{MPP} pair, while its variation suggests the direction and intensity with which this point moves [8]. The premises for tracking could be developed which were then used to build the controller's rule table. The main ones are defined as:

- IF The MPP is achieved when the error is zero:
  - THEN The voltage must remain at the point, so $\Delta D = 0$;
- IF $E > 0$ and $\Delta E < 0$, the point is to the left and approaches the MPP:
  - THEN The voltage approaches the value corresponding to the MPP (increases), so $\Delta D = 0$;
- IF $E > 0$ and $\Delta E > 0$, the point is on the left and moves away from the MPP:
  - THEN The voltage moves away from the value corresponding to the MPP (decreases), so the $\Delta D < 0$;
- IF $E < 0$ and $\Delta E < 0$, the instantaneous point is on the right and moves away from the MPP:
  - THEN The voltage moves away from the value corresponding to the MPP (increases), so $\Delta D > 0$;
- IF $E < 0$ and $\Delta E > 0$, the instantaneous point is on the right and approaches the MPP:
  - THEN The voltage approaches the value corresponding to the MPP (decreases), so $\Delta D = 0$.

When considering the relevance of pertinence functions, the following principle was applied to determine them: when MPP is far, the increments must be large. As it approaches, the increments are gradually reduced until they cancel out at the precise point. Thus, the pertinence functions and their respective universes of discourse were defined: E, $\Delta E \ \epsilon \ [-5{,}5]$ and $\Delta D \ \epsilon \ [-0.001{,}0.001]$. Where, the pertinence functions of the inputs are similar, differing only for Z (ΔE, dashed), according to Fig. 2(a), and the pertinence function of the output, according to Fig. 2(b).



((a)) Inputs E and ΔE ((b)) Output ΔD

Figure 2. Membership functions

These define the possibility of fuzzy inference for a Duty jump up to 10 times greater than the fixed step of the incremental conductance method. Additionally, for the same purpose, rules corresponding to zero error were assigned a weight of 1, whereas other rules were assigned a weight of 0.3. It is important to note that the adjust of these values was achieved experimentally, where the values were varied and their influence on the system's response was verified.

6 Results

As a basis for comparing the two MPPT methodologies, three test scenarios were defined in which the system is disturbed by abrupt variations in temperature and solar irradiance. The aim was to analyze the Fuzzy and IC MPPT systems in two extreme scenarios to evaluate the robustness of the tracking methods. In scenario 1, the PV irradiation was kept at 1000 W/m², and starting at 50°C, the temperature was varied in 4 steps of -10°C. In scenario 2, the PV temperature was kept at 25°C, and the irradiation was varied in 4 steps of -200 W/m², starting at 1000 W/m². As a standard, in each scenario, the steps were implemented at time intervals of 0.5 seconds, which was suitable for tracking and signal stability.

Figure 3 contains the tracking results of the IC and Fuzzy MPPT methods. As can be seen, the fuzzy MPPT's tracking time is shorter than the IC's. This is evidenced in the detail of step 1, where it is possible to observe the moment where the moving averages meet the tracking criterion, remaining within the limit of 0.1% of P_{MPP}. This is because scenario 1 considers temperature variations, making the voltage jumps corresponding to each step's MPPs (V_{MPP}) larger. Therefore, in this scenario, the fuzzy MPPT has an advantage over the IC due to its variable duty-cycle increment in power variation.

Additionally, regarding power ripple on MPP, a greater ripple amplitude is observed for the IC MPPT method. This is also due to the fuzzy MPPT being able to decrease the duty-cycle increment as it approaches the MPP progressively. Finally, efficiency can be seen in the difference between the theoretical MPP reference signal (red) and the signals for each method, Fuzzy MPPT (blue) and IC MPPT (green). So the efficiency was calculated and accounted for according to eq. (10) and in Table 2, respectively. Where IAE is the Integral Absolute of Error, taking the whole scenario into account.

$$\eta\% = \frac{1}{(1 + IAE)} \cdot 100\% \tag{10}$$

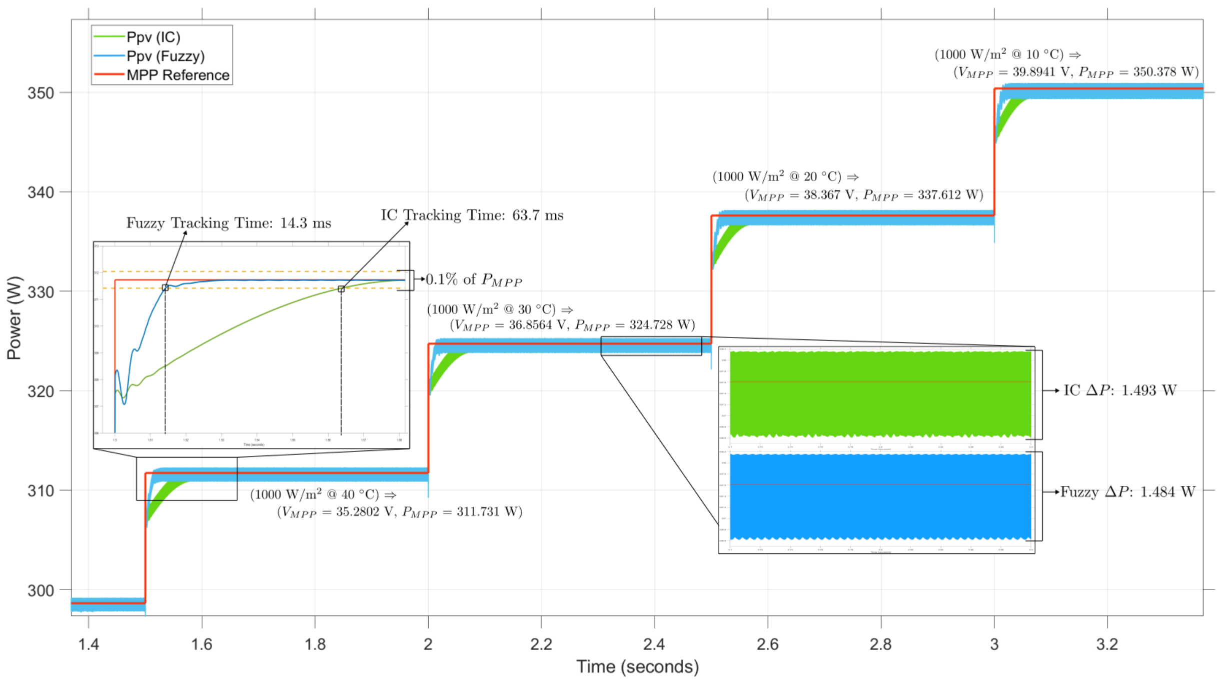


Figure 3. Scenario 1 Fuzzy and IC MPPT response

Figure 4 contains the tracking results of the IC and Fuzzy MPPT methods. Scenario 2 considers variations in solar irradiation, making the voltage jumps corresponding to the MPPs of each step smaller than in scenario 1. However, the variations in irradiation have a more significant impact on the P_{MPP} values of each step. Therefore, in this scenario, the fuzzy and IC MPPTs perform closely regarding of efficiency and tracking speed, as can be seen in the test overview.

In the detail of the first step, it can be seen that the IC MPPT has a shorter tracking time than the Fuzzy MPPT, according to the criteria. However, the details of step 3 show the opposite. This is due to the Fuzzy's variable increment being dependent on power variation. In contrast, the fixed IC increment is enough to quickly track the MPP since V_{MPP} does not change much from one step to the next. Therefore,

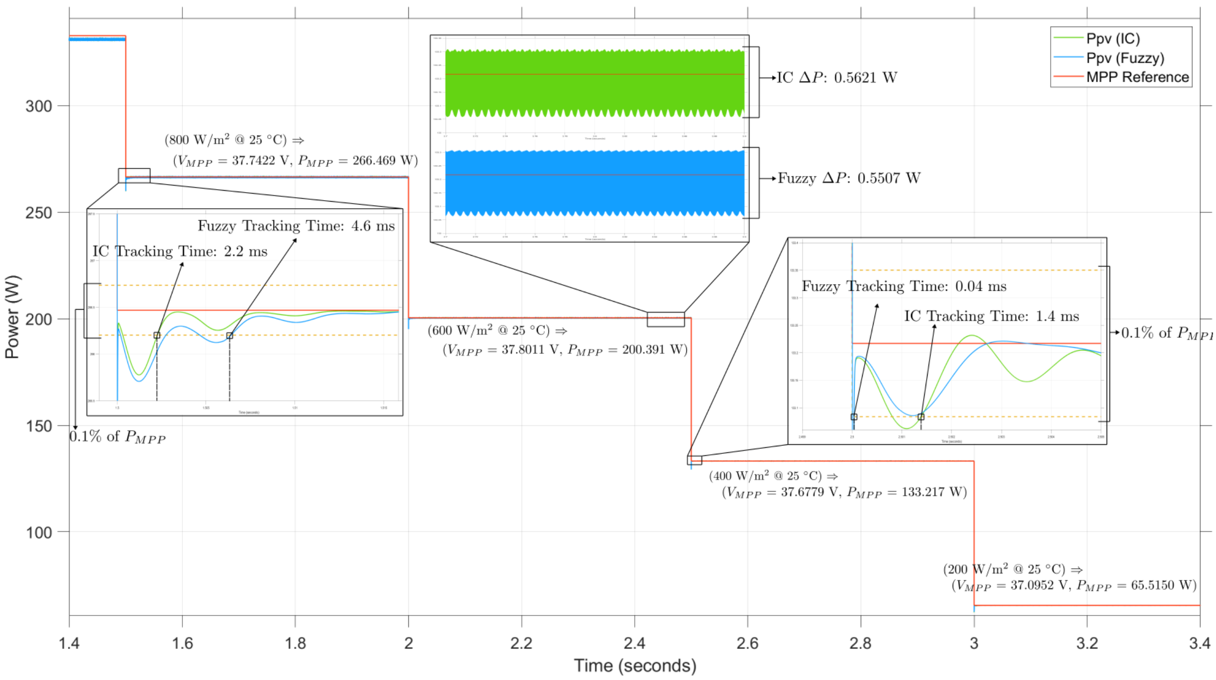


Figure 4. Scenario 2 Fuzzy and IC MPPT response

as the solar irradiation decreases, the variation in power also decreases, and the techniques are equally efficient according to the criteria. However, the Fuzzy MPPT is faster for lower solar irradiations.

	MPPT	Tracking Time (ms)				ΔP (W)				η (%)
		Steps				Steps				
		1	2	3	4	1	2	3	4	
Scenario 1	fuzzy	14.3	13	17	18	1.423	1.484	1.545	1.62	92.23
	IC	63.69	56	54	48	1.429	1.493	1.558	1.62	92.05
Scenario 2	fuzzy	4.6	2.43	0.04	4.7	0.9755	0.5507	0.2435	0.7872	93.61
	IC	2.2	2.17	1.4	9.3	0.9923	0.5621	0.2509	0.5686	93.62

Table 2. Overall Results of the Performance Parameters

Fuzzy MPPT has a shorter tracking time than IC MPPT for abrupt temperature variations, while for solar irradiance variations have equivalent tracking times. As mentioned above, in scenario 1, the tracking time of the Fuzzy MPPT was lower in all steps, while in scenario 2, in steps 1 and 2, the IC MPPT obtained a better result, while the Fuzzy MPPT obtained better results in the rest. In general, the permanent power ripples of the fuzzy MPPT were slightly smaller than the IC MPPT due to the variable increment. In scenario 2, the power fluctuations are less significant because the P_{MPP} values are lower, generating more minor power fluctuations in the permanent regime. Finally, the tracking efficiency of Fuzzy MPPT is higher than IC MPPT in scenario 1 due to the variable increment and is equivalent to IC MPPT in scenario 2. Therefore, Fuzzy MPPT can track the MPP more quickly in temperature variations, where the value of V_{MPP} varies more; it also performs equally well in scenarios where the values of V_{MPP} are closer, in the case of solar irradiance variation.

7 Conclusions

This work proposes an MPPT technique based on fuzzy logic with a variable duty-cycle increment, compared to a classic IC MPPT technique with a fixed increment. Both techniques were applied to a solar battery charger system with a Buck converter, implemented by simulation in the MATLAB/SIMULINK software environment.

It was found that the fuzzy MPPT technique performed better than the IC MPPT in supplying energy to the batteries more efficiently under different operating conditions, based on performance parameters found in the literature, such as tracking time, efficiency and power ripple on MPP.

This was due to FIS's ability, as opposed to the IC method's fixed increment, to implement a variable increment and, therefore, to reach the MPP more quickly in the scenarios that required more significant variations in the voltage applied to the panel, impacting the tracking time. As MPP gets closer, it reduces the increment to zero, impacting the efficiency and steady-state oscillation.

Future work will focus on applying bio-inspired optimization algorithms to tune the fuzzy MPPT, considering tracking efficiency as a cost function.

Acknowledgements. This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoa de Nível Superior–Brasil (CAPES)-Finance Code 001. The authors thank the Brazilian National Council for Scientific and Technological Development (CNPq), for their financial support.

Authorship statement. We, the undersigned authors, jointly declare that we have contributed equally to the conception, development, and drafting of this work. Each author has participated in research, data collection, analysis, writing, and critical review equally. We collectively assume full responsibility for the content presented in this work.

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